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A Novel Collaborative IoD-Assisted VANET Approach for Coverage Area Maximization

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ABSTRACT Internet of Drones (IoD) is an efficient technique that can be integrated with vehicular ad-hoc networks (VANETs) to provide terrestrial communications by acting as an aerial relay when terrestrial infrastructure is unreliable or unavailable. To fully exploit the drones' flexibility and superiority, we propose a novel dynamic IoD collaborative communication approach for urban VANETs. Unlike most of the existing approaches, the IoD nodes are dynamically deployed based on current locations of ground vehicles to effectively mitigate inevitable isolated cars in conventional VANETs. For efficiently coordinating IoD, we model IoD to optimize coverage based on the location of vehicles. The goal is to obtain an efficient IoD deployment to maximize the number of covered vehicles, i.e., minimize the number of isolated vehicles in the target area. More importantly, the proposed approach provides sufficient interconnections between IoD nodes. To do so, an improved version of succinct population-based meta-heuristic, namely Improved Particle Swarm Optimization (IPSO) inspired by food searching behavior of birds or fishes flock, is implemented for IoD assisted VANET (IoDAV). Moreover, the coverage, received signal quality, and IoD connectivity are achieved by IPSO's objective function for optimal IoD deployment at the same time. We carry out an extensive experiment based on the received signal at floating vehicles to examine the proposed IoDAV performance. We compare the results with the baseline VANET with no IoD (NIoD) and Fixed IoD assisted (FIoD). The comparisons are based on the coverage percentage of the ground vehicles and the quality of the received signal. The simulation results demonstrate that the proposed IoDAV approach allows finding the optimal IoD positions throughout the time based on the vehicle's movements and achieves better coverage and better quality of the received signal by finding the most appropriate IoD position compared with NIoD and FIoD schemes.

INDEX TERMS Internet of Things, Internet of Drones, intelligent transportation system, vehicular ad hoc networks, improved particle swarm optimization.

I. INTRODUCTION

Recently, Intelligent Transportation Systems (ITS) have received significant attention as a leading technology to exploit the smart devices involved in the transportation object that improves transportation systems. The importance of the ITS lies in many factors, such as increasing the global population, globalization, and modernization, which lead to high demands for vehicle transportation. Furthermore, the harmful effects on the environment and awareness are raised due to the congestion and inefficient vehicles. It is worth mentioning that the promising development in telecommunications and computing technologies has accelerated the researches towards smart transportation [1]. This fast growth of paradigm is characterized by an open architecture that allows transportation objects to interact and cooperate in executing a wide range of tasks [2]. Besides, enabling a plethora of applications such as intelligent guidance and collision avoidance provides comfort and convenience as well as increases safety during driving. Therefore, the ITS is expected to play a significant role in future smart cities [3].

In VANET networks, the vehicles are allowed to move in the path and able to communicate with stationary stations and with each other alongside the path which is the main idea

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behind the VANETs. Although, ITS provides essential services in which most of them mainly rely on connectivity and communications among vehicles, the links between vehicles could be lost due to path loss or severe shadowing. In this regard, ITS's serious challenge arises because of frequent topology change of VANET due to the dynamic movement of vehicles where the connectivity of a vast number of vehicles is always intermittent [3]–[5]. Besides, the link quality is another challenge in VANET, where communication technology such as 802.11p is highly sensitive to obstacles and distance.

Recently, drones, known as Unmanned Aerial Vehicles (UAVs), have seen significant consideration for numerous applications, including surveillance, military, telecommunications, medical supplies delivery, rescue operations, and monitoring [6]–[9]. Due to their unique features such as agility, mobility, and flexibility, UAVs offer high freedom of movement that allows UAVs to navigate remote and rough areas that humans cannot access.

The Internet of Drones (IoD) term is an integration of drones into a network of IoT [10] and defined as a layered network control architecture designed mainly to coordinate UAVs' access to control airspace and provide navigation services between locations known as nodes [11]. In these applications, IoD can support an efficient mean not only to enhance traffic policy in the ground and enforce traffic rule, but also to provide efficient information dissemination to the ground users.

The IoD paradigm offers a significant feature which is its ability to have line-of-sight (LOS) connections toward the users due to drones' elevations. That is, when traditional ground networks are damaged, UAVs can support efficient and effective temporary communication networks [12]. Unlike ground nodes that have to follow a specific route, the nodes in IoD can move freely in three-dimensional space and fly above high buildings which may obstruct the ground vehicle's communication. Thus, the LOS communication can be established effectively by adjusting the drones' altitudes and mitigating shadowing and signal blockage. Towards this end, dedicated UAVs are employed as aerial access points (APs), relays, roadside units (RSUs), or base stations (BSs) to provide wireless ground network communications, which is called UAV-assisted wireless communication. The UAV-assisted has become an alternative connection for ground vehicles [13] and attracts the attention of extensive researchers [14], [15].

Based on the above tremendous advantages of drone, vehicular to vehicular (V2V) communication, which is a kind of device to device (D2D) communication [16], [17], can be supported by IoD network when a direct multi-hop link between vehicles is not available. In this case, IoD can be utilized as a relay network to maintain the reliable wireless communication links between vehicles on the ground [18]. Besides, the wireless network's performance can be improved significantly using IoD in different scenarios such as emergency situations and temporary hot-spots when acting as flying RSUs or BSs.

The interconnected nodes in the IoD network make it fault tolerance and robustness. Furthermore, the interconnected IoD network can be easily integrated with other networks and fast deployed in difficult conditions to provide the communication in which ground infrastructures get damaged or the manually deploying them are almost impossible. In this case, temporary communication is provided to connect the disconnected targets in that area [19]. Coverage problems with ground vehicles have been examined extensively in the literature. Moreover, the harsh terrains can significantly limit the maneuverability of ground mobile vehicles. Generally speaking, two main factors affect the connectivity of IoD and ground network namely LOS and the path loss. It has to stress that deploying IoD at high altitude enhances LOS condition but increases the distance between sender and receiver which in turn increases the path loss. To maintain the range of the received signal and achieve LOS, IoD positions should be optimized using an appropriate mechanism.

In this paper, we propose implementing an optimization algorithm to obtain the optimal deployment of IoD in a dynamic vehicular communications environment. The adopted deployment of IoD at any instant of time allows providing communication between vehicles on the ground. We consider the coverage as the number of vehicles covered by the IoD network. Such an optimum deployment is determined by considering the current locations of ground vehicles and can be evaluated by considering the quality of the received signal at the receivers, i.e., vehicles on the ground.

The main contribution of this work is utilizing IoD as a relay network at optimum coverage base-on cars' locations using Received Signal Strength Indicator (RSSI). In this work, the improved version of the Particle Swarm Optimization (IPSO) algorithm in [2] is implemented to achieve the aforementioned objectives so that sufficient signal strength towards all isolated vehicles on the ground can be achieved by the IoD network to guarantee the best coverage at each specific time. Moreover, the connectivity of the IoD network is addressed by the proposed optimization approach where the objective function includes the connectivity to be achieved for a better solution. Furthermore, we design an IoDAV to boost the VANET communication performances. Based on the vehicles' distribution on the ground, the proposed approach dispatches the IoD nodes to the most appropriate locations in real-time. The main assumption is that lack of infrastructures exists in the environment and the connectivity among vehicles is minimum. For example in urban area, the buildings may obstruct the line of sight and the connectivity among vehicles is lost. Besides, the movement of UAVs in IoD aims to explore the 3D space to offer the connectivity to the ground vehicles.

The contributions of this work can be summarized as follows:

1. A novel collaborative IoD architecture is proposed and integrated with VANETs. For a specific location, the demand for UAVs is evaluated using an optimization evaluation

function to obtain the optimal deployment of IoD to assist the VANET.

2. The population optimization scheme is designed to improve the proposed model. The optimization scheme has enabled the IoD nodes dispatching to the best service locations and maintains the connectivity constraint of the IoD network so that the efficiency of IoDAVs approach is enhanced.

3. Extensive simulation experiments are conducted to test the model performance and to evaluate the proposed model. The simulation results are discussed and analyzed in detail.

The rest of this paper is organized as follows: Section II presents the literature review. In Section III, the IoDAV mechanism description is illustrated. Section IV explains the optimal IoD deployment which includes the formulation of IoDAV and Optimization problem. Section V discusses in detail the population optimization for coverage. The framework of optimization is illustrated in section VI. In section VII the simulation results and the corresponding analysis are discussed. The work is finally concluded in Section VIII.

II. LITERATURE REVIEW

Recently, various technologies have been introduced to complement the services of the Internet of Things (IoT) [20]. The deployment of UAVs in IoT [21] offers unprecedented potentials. In this section, we review several mechanisms used to improve the coverage of the target area and UAVs-Assisted VANETs. The deployment strategy has become useful in wireless networks to obtain the best performance [22]. we classify the literature into two types namely, RSU Deployment and UAVs Assisted Deployment.

A. RSU DEPLOYMENT

In [23], the placement algorithm of BS was proposed for network capacity maximization. However, the information dissemination performance can be impacted by node placement, acting as a relay node. In [24], the authors discussed the optimal placement of RSU to improve the intersection connectivity. The best position of RSU can be found by the proposed scheme using the reports from vehicles within the RSU communication range. In [25], the RSU deployment to maximize the number of connected vehicles is proposed. The average report time from vehicles is minimized by the placement strategy proposed in [26]. Nevertheless, the terrestrial obstacles hinder the transmitted signal when located between sender and receiver which limits Vehicles-to-infrastructure (V2I) communication. The flying RSU is a promising technique to cope with terrain obstacles and provide communication between vehicles on the ground which can be achieved using UAVs.

B. UAVs ASSISTED DEPLOYMENT

The UAV has the potential for acting as wireless BS or RSU to relay information between nodes in the ground networks especially when the terrestrial infrastructure capacity is not adequate for request handling in hot-spot areas. Furthermore, in remote and harsh environments, deploying ground BSs becomes difficult and inefficient. Such an environment can be covered using drones to extend the coverage of the network.

To tackle the limitations of low energy IoT nodes, UAVs are employed in [27] as a data collector and energy supplier. An efficient deployment approach to support better coverage for the ground users is proposed in [28] in which drones are considered as wireless base stations. The probability of download coverage is defined as a function of the UAV's height and antenna gain. Furthermore, the circle parking theory is used, and the 3D locations of drones that maximize the drone's lifetime and achieve the maximum coverage for the whole region are calculated. Nevertheless, to avoid the interference issue, the drone's height should be defined based on the directional antenna's beamwidth and the coverage requirements. The work in [29] analyzed the optimal deployment of UAVs in a multi-level and multi-dimensional assisted network. The distributed approach was based on a potential game approach. Moreover, self-organized behavior where local and global policies participated in decision making for each UAV was utilized

Recently, significant progress has been made in population-based evolutionary algorithms to obtain the best position of UAVs to assist the ground network. In [30], the authors propose an optimization for resource allocation and joint access selection where UAVs are acting as aerial BS. The ground BS allocates its resource based on the access selection decision of UAV. Based on allocated communication resources, drones decide their selection strategy. In [31], a 3D placement strategy of UAV is proposed by optimizing the problem for coverage and throughput maximization with the drone's memory constraint consideration. The optimization problem is divided into two parts. The first part aims to obtain the optimal position of the drone and the second part solves the optimal caching strategy. The authors in [32] proposed a mechanism to obtain the best position of drone in a disaster scenario to support the nodes' connectivity in indoor buildings. A strategically located drone is utilized to cover all users inside the building so that the minimum transmitted power is maintained. In [33], the optimal placement of UAV can be obtained using Particles Swarm Optimization (PSO) algorithm. The aim of the work is to maximize the coverage area while the drone capacity is still considered in the scope of the disaster and public safety. In [34], the brainstorm optimization algorithm is used to obtain the optimal position of UAVs for coverage quality improvement of the network. Furthermore, the use of the available number of UAVs was mentioned in [35] for covering all the targets while minimizing the rate of data dissatisfaction between end devices and their communication services. However, their research work didn't include it. In [36], the bio-inspired algorithms with multi-objective were proposed to obtain the optimal UAVs flight path. The proposed algorithm included several objectives such as energy, sensing ability, associated risk, and flight time. Moreover, the optimal height of a 3D placement of available UAVs is illustrated in [37]. The authors consider three objectives to be optimized namely target coverage, Quality of Service (QoS), and energy consumption. Furthermore, four optimization algorithms are utilized to solve placement problems. To maintain the connectivity of UAVs, the authors create a grid-based connectivity network called Aerial Mesh Network (AMN). However, they consider only static coverage in which drones hover to a given target area. Also, the covered targets are static (i.e they don't move during the mission). Additionally, the work optimizes the altitude of drones to generate a near-optimal height deployment of drones to cover the target devices and achieve QoS and minimum transmission data energy consumption.

In urban terrain, the infrastructures and buildings constrain the communication and movement of vehicles [38]. The use of drones in VANET assisted achieves a great improvement in the VANET connectivity, because the UAVs can fly at a high altitude beyond all the infrastructures of terrestrial allowing the movement of UAVs to be much less influenced by terrestrial constraints. Furthermore, fewer influences on the drones' transmission in the air can be generated by terrestrial obstacles. Based on these advances, UAV becomes an appropriate VANET assistant. Various schemes on the deployment of UAVs to support the vehicular communication are proposed. The author in [39] proposed a drone position algorithm in which the quality of services communication is offered to vehicles in the ground.

To obtain the optimum connectivity between the drones and vehicles, the best position of the UAVs so that adequate signals can be transmitted to the ground vehicles is needed. In paper [40], an urban VANET routing solution was proposed. It ensured reliable and alternative paths when the path failed. Further, in [41], the incidents are detected on the urban road by deploying the UAVs to provide the vehicle emergency guidance. Moreover, the end-to-end delay is reduced among cars by designing a hybrid vehicle drone ad-hoc network in [42]. In paper [43], the deployment of LTE connectivity for drones is studied. Some challenges are highlighted such as LOS propagation in the sky. In [44], the terrestrial infrastructure is replaced with a drone to minimize the V2I delay on the straight road. The authors in [45] proposed using a drone to improve the packet delivery ratio and reduce the delay. In [46], the drones are used to select the optimal path as an alternative path to achieve the stability and distribution of the cars.

In conclusion, some previous works achieved improvements in ground network performance such as coverage, throughput, routing, and end to end delay. Other works focused on maximizing coverage area based on download facing camera. Others achieved improvements in VANETs performance, but focus on routing protocols, or considered the static ground infrastructure. Generally, the full exploitation of superiority of drones to minimize isolated cars is omitted or neglected in the previous work.

Our proposed approach aims to design the IoDAV to boost the VANET communication performances. Based on the distribution of vehicles on the ground, the proposed approach dispatches the IoD nodes (UAVs) to the most optimized locations dynamically in real-time. The optimal deployment of the IoD nodes is determined to maximize the coverage area (i.e minimize the number of isolated vehicles on the ground). Additionally, the deployment of IoD nodes is adjusted to adopt the dynamic movement of vehicles on the ground.

III. IoD-ASSISTED VANET MECHANISM

As discussed in section II, the reviewed work related to VANET intended to enhance the performance of the VANET network, however, the UAV's mobility superiority was neglected. By controlling a few numbers of UAVs in a wide area, several infrastructures can be dispensed. Therefore, the VANET can be assisted by leveraging dynamic UAVs. As shown in Fig.1, an IoD-Assisted-VANET model consisting of the VANET network and IoD network is proposed. The VANET network consists of terrestrial vehicles on the ground and their mobilities are restricted by predefined roads and traffic regulations. Additionally, the quality of communication is impacted by the surrounding environment. The IoD network, which is integrated with VANET, consists of UAVs swarm with wireless communication. The UAVs swarm are responsible for supporting the connectivity among vehicles. Thanks to their flexible mobility, they can be easily dispatched to the most appropriate locations where the relay is required among vehicles. Fig.1 illustrates the effectiveness of the proposed IoDAV architecture in which the vehicles cannot communicate directly within their communication range. The buildings are considered as obstacles and hinder the transmitted signal. Thus, UAV1 and UAV2 are dispatched to suitable positions, where vehicles are isolated by building and can neither communicate nor transmit data to infrastructure. The two UAVs act as a relay to create a connection among those separated vehicles.

It is noteworthy that the positions of UAVs are updating periodically based on the movement of ground vehicles and the state of received signal therein. The UAVs are first dispatched to the appropriate locations and then hover therein to provide communication among isolated vehicles. As the vehicles move, the distance between them increases and they might be isolated by obstacles lying between them, which in turn lose the connection. Then, the IoD's location is updated to connect the isolated vehicles.

IV. OPTIMAL IoD DEPLOYMENT

In this section, we will describe the formulation of IoD deployment. Particularly, we will explain how the optimization algorithm addresses the drone's positions as well as the optimization algorithm used.

A. PROBLEM FORMULATION OF IoD-ASSISTED VANET

The deployment of drones has been impacted by their coverage, which can be classified into static and dynamic coverage. In the former, the UAVs hover in the target region during the whole mission time. The complete design goal, such as maximizing the coverage area, has to be achieved in the deployment. In the letter, the UAVs keep changing

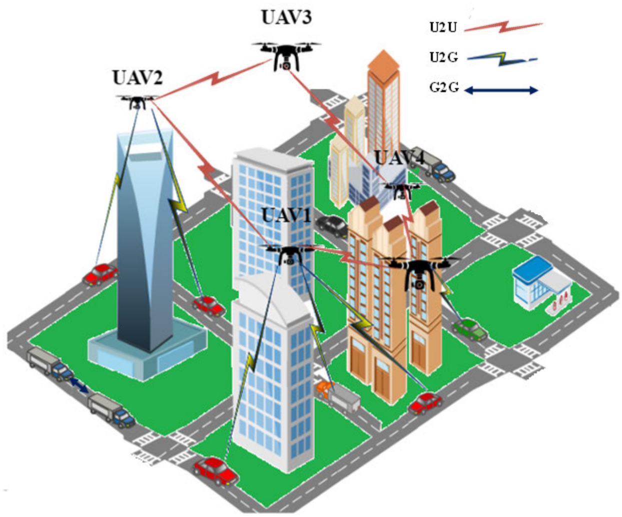


FIGURE 1. IoD-assisted VANET architecture.

their positions during the mission depending on the current locations of ground nodes. Besides, we focus on dynamic deployment with the aim of maximizing the coverage area in a 3D environment. To do so, we consider the scenario including many vehicles that follow specific paths on the existing region. Also, in the considered scenario, the area lacks sufficient infrastructures and the IoD will help to relay the information among vehicles. It is noteworthy that the locations of IoD nodes are changing throughout time depending on the locations of ground vehicles. At every time step, when the vehicles on the ground move, the new optimal locations of IoD have to be evaluated.

B. OPTIMIZATION PROBLEM

Our main objective is to obtain the best position of interconnected IoD network in a 3D environment so that the transmitted signals from IoD nodes can be received by all Isolated vehicles in the ground with sufficient power reception. Such dynamic deployment requires an efficient technique to dispatch the drones to the optimal locations. Furthermore, obtaining the best locations of IoD nodes by trying all possible locations in the space at each time step is an inefficient way. This is because it consumes a lot of resources and takes a lot of time which is considered as an NP-hard problem.

The sophisticated solution is to use a meta-heuristic algorithm where the optimal solution can be obtained without testing all possible values. Instead, the random position is generated and evaluated using the fitness function. Then the iterative manner is used to search for the best possible solution. Among those population-based, PSO, swarm intelligence algorithms, is one of the intelligent algorithms employed in the deployment problem. In this work, we consider the dynamic coverage using the improved version of intelligent optimization technique i.e IPSO.

The RSSI metric in the received vehicles is utilized by the objective function to evaluate the generated positions and the best positions of IoD nodes are selected. On the receiver side, the RSSI is selected and compared with the minimum threshold. In our work, the minimum threshold is defined to be −86dBm (the threshold for successful packet delivery). Particularly, to achieve full coverage connectivity, the average RSSI should be greater than the minimum threshold. More importantly, the RSSI metric is utilized to calculate the number of covered vehicles in the ground by the IoD network. At each vehicle, we analyze the RSSI when the positions of IoD nodes are selected. Then the vehicle is counted to be covered if RSSI is greater than the minimum threshold. In the next section, the optimization algorithm utilized in our work is explained in detail.

V. IMPROVED PARTICLES SWARM OPTIMIZATION FOR COVERAGE

To address the formulated problem, the IoDAV approach has to work in real-time. In this context, we propose an effective population scheme, IPSO, for IoDAV to design the feasible collaborative approach. The IoDAV dispatches multiple UAVs to different positions for optimal deployment. Obviously, this approach is designed to integrate the IoD network with the VANET network for assistant in infrastructure-less scenarios that need relay nodes for communication. IPSO is an enhanced version of traditional PSO. It avoids trapped in local optima and searches for the global optima in a more accurate and faster way. The enhancements are improving the initialization stage by using uniform initial distribution as in eq.1.

$$X_{n+1} = \mu X_n(1 - X_n), \tag{1}$$

where X_n represents the n^{th} chaotic variable, μ is a bifurcation coefficient. Then the velocity is updated using

$$v_{t+1} = \omega v_t + c_1 r_1(pBest_t - x_t) + c_2 r_2(gBest_t - x_t), \tag{2}$$

where c1, c2 are acceleration coefficients, r1, r2 are random variables, and ω is an inertia weight. The position of each particle is updated using

$$x(t + 1) = x(t) + \epsilon v(t + 1), \tag{3}$$

where ϵ selects how fast the particle moves. Furthermore, the parameters Inertia Weight (ω) and Epsilon(ϵ) are updated to balance global and local search using the following (4) and (5) equations respectively.

$$\omega(t) = \omega_{min} + \frac{MaxIt - t}{MaxIt} * (\omega_{max} - \omega_{min}), \tag{4}$$

$$\epsilon = \epsilon_{max} - \frac{(\epsilon_{max} - \epsilon_{min})t}{MaxIt}, \tag{5}$$

where $MaxIt$ is maximum simulation time and t is current simulation time, ω_{min}, ω_{max} are minimum and maximum value of inertia, respectively, ϵ_{max}, ϵ_{min} are constant value and $\epsilon_{max} > \epsilon_{min}$.

The inactive particles are replaced by new fleshing particles to rich the diversification search of the algorithm.

The pseudo-code of IPSO for IoDAV is explained in the algorithm 1. The parameters of the algorithm such as acceleration coefficients c1 and c2 are initialized in the initialization part of the algorithm. The initialization part is also responsible to create the initial position and velocity of all particles. The algorithm receives parameters and environment constraints and returns the best locations of all UAVs that achieve the maximum coverage. For each iteration, the informant particles are assessed and the solution that achieves the best coverage is stored in LBest with the corresponding coverage and RSSI. The velocity and position of each solution are updated using eq.2 and eq.3 respectively. Then the fitness of generated solution is evaluated and compared with LBest solution. Moreover, the GBest is compared with LBest and the best overall solution is stored in GBest. Note that if two solutions achieve the same coverage, the solution with a higher average RSSI is selected as the best. Finally, the global solution that includes the best positions of IoD nodes with maximum coverage and RSSI is returned. It has to stress that the IoD is an interconnected network meaning that the GBest includes interconnected nodes of IoD.

VI. OPTIMIZATION FRAMEWORK

The IoDAV aims to enhance the connectivity of infrastructure-less VANET network by optimally deploying the IoD network. To this end, the sophisticated approach based on a meta-heuristic algorithm is implemented to dispatch the IoD nodes to the optimal locations and maintain the connectivity of the IoD network. The proposed approach is implemented in the OMNET++ tool [47] and the framework is illustrated in Fig.2. The new module is developed as an extension to the OMNET++ network simulator to implement the IPSO. The aim of this module is to optimally place IoD nodes so that the number of covered vehicles on the ground is maximized, i.e dispatching the IoD nodes to the most appropriate locations, in addition to maintain the connectivity of the IoD network. Furthermore, the map is generated using the SUMO NetEdit tool and the traffic simulator SUMO [48] is utilized to mimic the movements of vehicles on the ground. Besides, the information of mobility from SUMO is polled at fixed intervals. Moreover, for more realistic vehicles communications, the Veins simulator [49] is used. Whenever the departure of a mobile node is simulated by SUMO, the dedicated simulation module is created by Veins in OMNET++. Then, Veins updates the speed, position, and heading of the mobile node in the created module in OMNET++ as the mobile node moves in SUMO. Similarly, the OMNET++ module is removed from the simulator when the mobile node arrives at its destination in SUMO. This way, the mobility of node in OMNET++ is coupled to that in SUMO by Veins [50].

In light of the above illustration of the framework, the IoD deployment module receives the instantaneous locations of vehicles on the ground and dispatches IoD nodes to the most appropriate locations to maximize the number of covered vehicles and maintain the IoD network connectivity.

Algorithm 1 IPSO Algorithm for IoDAV

Input
Trail: Maximum Limit of trail
MaxIt: maximum iteration
PSize: Population Size
Bmin,Bmax: Environment Boundary
Output: Best Positions and fitness of IoD nodes (GBest)

INITIALIZATION:
initialize c1,c2
for each ($i \in PopSize$) **do**
  initialize position [Pos_i] with logistic map using Eq1
  $V_i = 0$
  $Fitness_i = Obj\_Fun(Pos_i)$
  if $Fitness_i$.Cov>GBest.Cov **then**
    GBest = $Fitness_i$
  end if
  if ($Fitness_i$.Cov==GBest.Cov) $\wedge$ ($Fitness_i$.RSSI>GBest.RSSI) **then**
    GBest = $Fitness_i$
  end if
end for
repeat
  iter=0
  while Iter<Max_Iteration **do**
    Update ω by Eq4
    Update ϵ by Eq5
    for each ($i \in PopSize$) **do**
      Update the velocity $V_i(t+1)$ using Eq2
      Update the position $Pos_i(t+1)$ using Eq3
      $Fitness_i = Obj\_Fun(Pos_i(t+1))$
      if $Fitness_i.Cov > LBest.Cov$ **then**
        LBest= $Fitness_i$
        if LBest.Cov>GBest.Cov **then**
          GBest =LBest
        end if
        if ($LBest$.Cov==GBest.Cov) $\wedge$ (LBest.RSSI>GBest.RSSI) **then**
          GBest=LBest
        end if
        Clear trail of generated Particle
      else
        Increment Particle trail (trail(i))
      end if
    end for
    for each ($i \in PopSize$) **do**
      if trail(i)>limit **then**
        Replace inactive particle by new fresh one.
        Clear its trail
      end if
    end for
    Increment Iter
  end while
until Ideal best is obtained or run out of time
return ($GBest$)

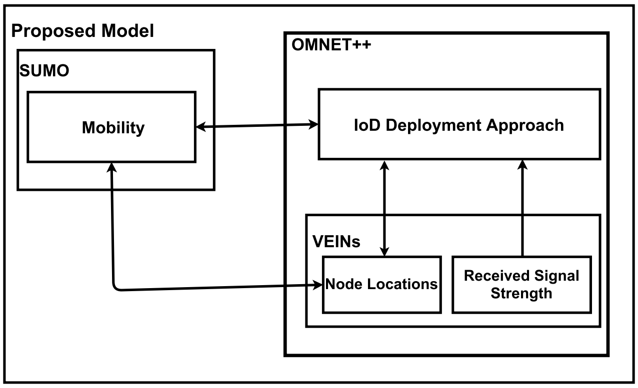


FIGURE 2. IoD-assisted VANET framework in OMNET++ network simulator.

The objective function of IPSO is composes of two parts: the first part,i.e objective, includes the quality of the received signal at the receiver side, i.e vehicles on the ground, which is obtained by path loss propagation model and the coverage of ground vehicles, while the second part, i.e objective, maintains the connectivity of IoD nodes. The aim is to achieve those two objectives. The output of IPSO is the optimal positions of IoD nodes that maximize the number of covered vehicles by the interconnected IoD network.

VII. SIMULATION RESULTS AND ANALYSIS

In this section, we show the effectiveness of the proposed IoDAV approach for achieving the optimal coverage in the dynamic environment. Throughout the obtained results, the influence of the IoD size and transmission power on the coverage and received signal strength are discussed. Moreover, the IoDAV is compared with standard VANET without IoD assisted, i.e NIoD, and FIoD, to show why the VANET needs IoD rather than BS. Considering the aiming of the proposed scheme to improve the VANET connectivity, the performance metrics adopted in the simulation are the average coverage and average RSSI. Without loss of generality, the coverage is normalized to unity.

A. PARAMETERS SETTING

The simulation parameters used throughout this work are abstracted in Table 1. This work considers the Two-ray Ground Reflection propagation loss model provided by OMNET++ with α value of 2. In this propagation model, the ground reflection path, as well as the direct path, are taken into consideration for calculating the received power. So, an accurate calculation is given for the received power in this model. The approved amendment to the IEEE 802.11 standard (802.11p) implemented in Veins to add wireless access in vehicular environments (WAVE) is utilized. The setting parameters of the drone's communication network based on OMNET++ simulation tool are set as follows: The geographical range is 4000m x 4000m. The simulation area is generated by the SUMO NetEdit tool and the vehicle movement is generated by the SUMO simulator. Moreover, the UDP packet is a Basic Safety Message (BSM) with a size of 1.4KB. The frequency band used is 5.9 GHz. The drones fly at 100m altitude. The simulation time is set to 400s, after which most of the vehicles in the ground reach their destinations, to test the behavior of the model. Moreover, the minimum threshold is defined to be −86dBm (the threshold for successful packet delivery). Each point in the figures represents the average of 10 replications of simulation. We implement two scenarios: sparse scenario (300 vehicles) and dense scenario (150 vehicles).

TABLE 1. Parameters setting.

Parameter	Value
Geographical Range	4000m x 4000m
Propagation Model	Two-ray Ground Reflection
α value	2
Frequency	2.9 GHz
IoD size	[2,4,6,8,10,12,14,16,18,20] UAVs
Drone's Altitude	100 m
Transmission Power	(20,30,40,50) mW
minPowerLevel	-86dBm
Optimization Approach	IPSO
Population Size	50
Maximum Iteration	50
Packet Size	1.4KB
Message Type	BSM
sending rate	1Hz
Update Interval	10 s
Simulation Time	400s

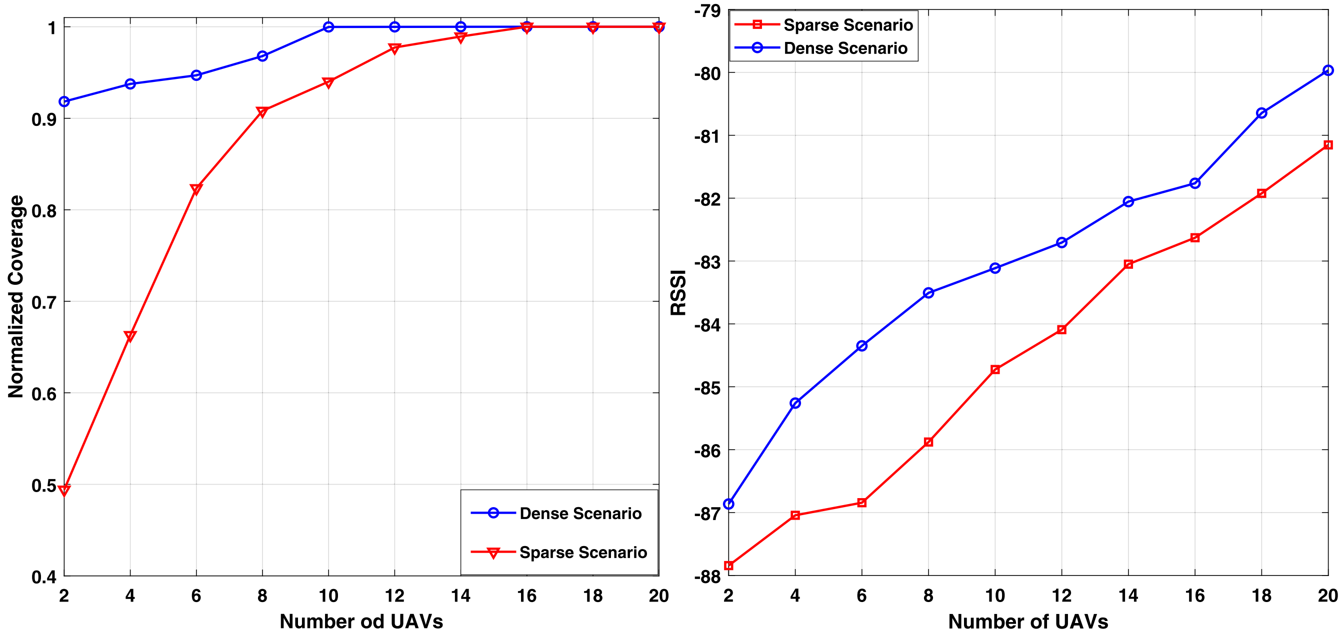
B. IMPACT OF IoD SIZE ON VANET CONNECTIVITY AND RSSI

The IoD nodes have been deployed to provide wireless coverage to ground vehicles. The coverage is a percentage of connected vehicles and can be calculated by $V_C/\mathbf{V}$, where V_C is the connected vehicles, and $\mathbf{V}$ is the total vehicles on the ground. It can be replaced by isolated vehicles which is equal to $\mathbf{1\text{-}V}_C/V$. In this subsection, we will discuss the normalized coverage with respect to different IoD sizes in both sparse and dense scenarios.

The IoD size (different sets of UAVs in IoD) implemented are (2, 4, 6, 8, 10, 12, 14, 16, 18, and 20 UAVs) with transmission power of 50mW. The simulation result is illustrated in Fig.3.

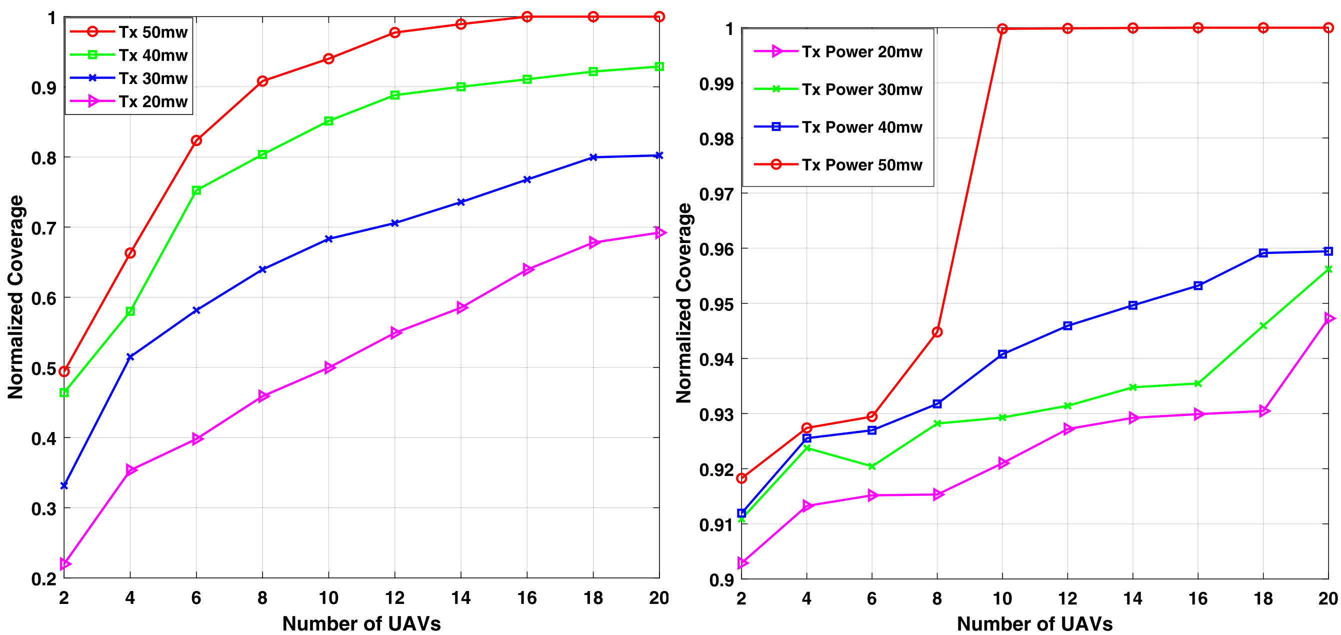
We can observe from the figure that the IoD enhances the connectivity of the VANET network. This trend increases as the number of drones increases with the same transmission power used, demonstrating the size effect of the IoD network on coverage. However, increasing the IoD size might increase the interference and the probability of collision with adjacent drones. Besides, when the drones are too close to each other, they become redundant drones and play the same role. Thus, sufficient distances within their communication ranges should be maintained which is considered in the IoDAV approach. Furthermore, sufficient isolated vehicles appear due to their imbalance distribution and frequent movement.

In the dense scenario, the vehicles are close to each other and most vehicles can directly communicate within their communication range, demonstrating that the number of isolated vehicles appears with a low number and requires fewer IoD nodes to provide the connectivity among them, while in



(a) Normalized coverage (b) Average RSSI

FIGURE 3. The average normalized coverage and RSSI for different IoD sizes in the IoDAV approach.

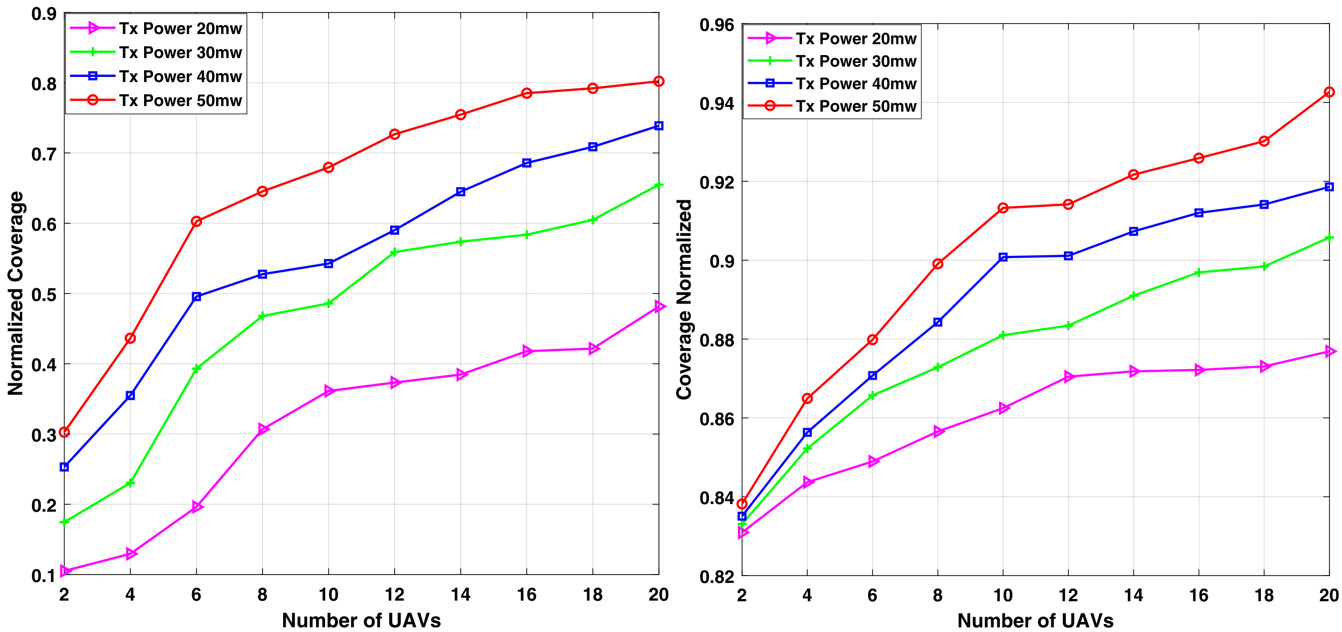


(a) Sparse scenario (b) Dense scenario

FIGURE 4. The average normalized coverage for different transmission power values with respect to different IoD sizes in the IoDAV scheme.

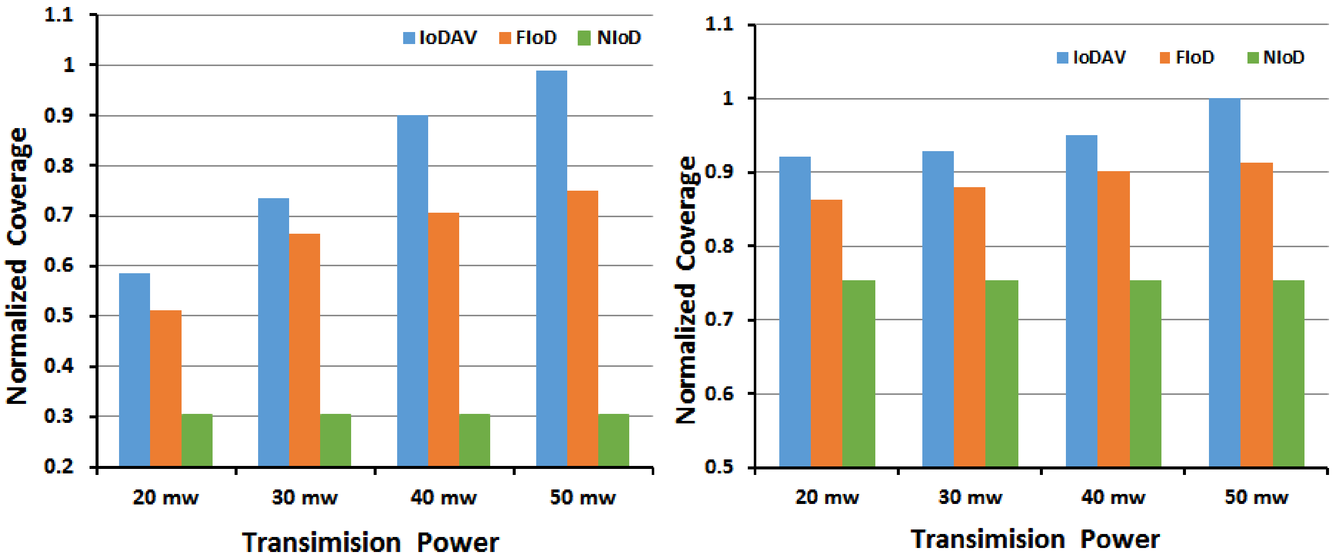
the sparse scenario, the vehicles are far from each other and number of isolated nodes appears with a high number and requires a higher number of IoD nodes for connecting them. This fact can be easily figured out by considering Fig.3. It can be seen that the maximum coverage is almost reached using 10 drones in the dense scenario and 16 drones in the sparse scenario.

To further evaluate the performance of the proposed IoDAV approach, we also discuss the impact of IoD size on RSSI at the receiver side, which is considered as an indicator of key performance. Particularly, RSSI is measured with respect to the simulation time and the average RSSI result is shown in Fig.3b. The figure illustrates the average received signal quality at different receiver vehicles. It turns out that the quality of the received signal is lower in the beginning when only two UAVs are available, and it is improved as the IoD size increases. This advantage tends to grow higher in the dense scenario than in the sparse ones.



(a) Sparse scenario (b) Dense scenario

FIGURE 5. **The average normalized coverage for different transmission power values with respect to a set of UAVs in the FIoD scheme.**



(a) Sparse scenario (b) Dense scenario

FIGURE 6. **Average normalized coverage for different transmission power values in IoDAV, FIoD, and NIoD schemes.**

C. IMPACT OF TRANSMITTED POWER ON COVERAGE

To further investigate the effectiveness of proposed IoDAV model, the impact of transmitter power on the total coverage is discussed, and the results of both scenarios are depicted in Fig.4a and Fig.4b, respectively.

The figures present the normalized coverage versus IoD size with different transmission power (20, 30, 40, and 50mW) for both sparse and dense scenarios, respectively. As such, the impact of transmitter power on coverage is examined where coverage is observed to improve continuously with increased transmission power as expected.

It is clear from the figure that the higher the transmitting power, the wider the range, which leads to covering a larger number of vehicles, that, in turn, improves the overall coverage. This tendency is evident in both scenarios. In the sparse scenario, we notice that the highest normalized coverage is provided by using 20 drones with the transmission power of 20mW, 30mW and 40mW, reaches almost to 70%, 80%, and 93%, respectively, while it reaches to 100% in dense scenario using only 16 drones with a transmission power of 50mW. We also note that 10 drones are sufficient to cover all isolated vehicles using a transmission power of 50mW in

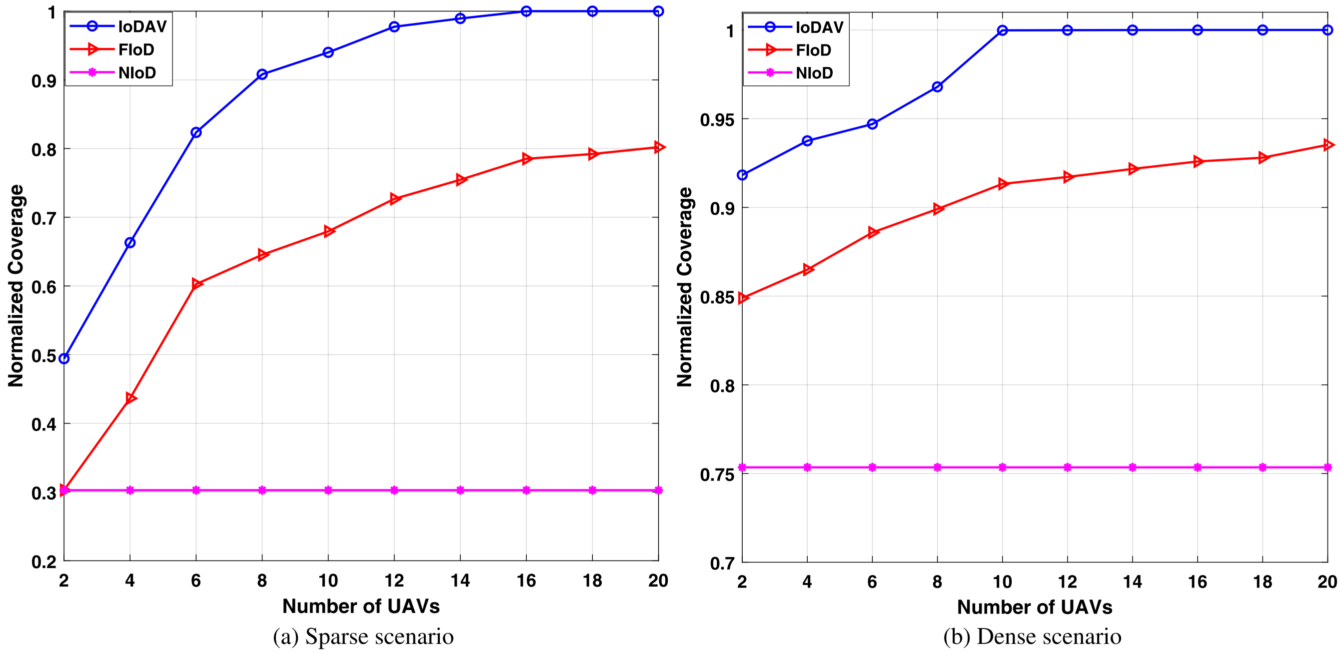


FIGURE 7. Average normalized coverage for different sets of UAVs in IoDAV, FIoD, and NIoD schemes.

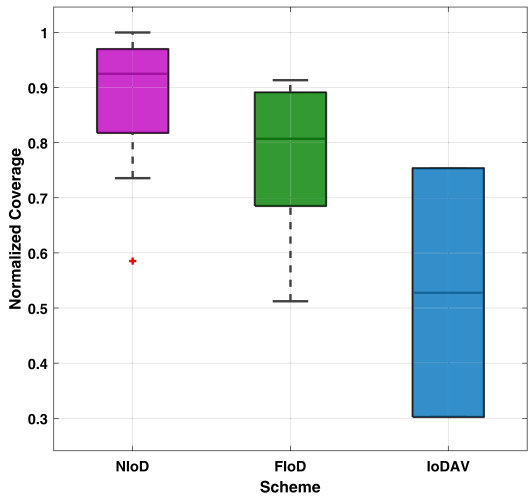


FIGURE 8. Box-plot of average normalized coverage in all scenarios for 10 UAVs in IoDAV, FIoD, and NIoD schemes.

the dense scenario, while the highest coverage achieved using the transmission power of 20mW, 30mW and 40mW reaches almost to 94%, 95% and 95.9% respectively.

For furthe investigating the effect of the transmitter power on improving coverage and reducing the number of drones required, we study the effect of the transmitter power in the FIoD model and the results are shown in Fig.5a, and Fig.5b. The same tendency as in the IoDAV approach, but the improvement in FIoD is not significant as in IoDAV. The maximum normalized coverage that can be achieved is 80% and 94% in the sparse and dense scenarios, respectively. Comparison will be discussed in the forthcoming subsection. To sum up, transmission power has a vital impact on improving the overall coverage as well as reducing the number of necessary drones.

D. COMPARISON WITH OTHER SCHEMES

We compare the proposed IoDAV approach against VANET without drone, i.e NIoD and with FIoD. Furthermore, the performance metric which is the normalized overall coverage and RSSI are considered in the comparison.

To investigate the performance of the proposed IoDAV, we study the normalized overall coverage with respect to transmission power for 10 drones (sufficient number of drones to cover all vehicles by IoDAV in the dense scenario).

The results of the comparison are exhibited in Fig.6a and Fig.6b for sparse and dense scenarios, respectively. It can be easily shown that IoDAV achieves better coverage than other schemes. This is because, in the NIoD scheme, there is no infrastructure used to connect the isolated vehicles. Additionally, in FIoD, the drones are deployed only once and the movement of vehicles on the ground is neglected. Whereas the proposed IoDAV approach considers the vehicle's current position every 10 seconds to obtain the positions of IoD nodes. Thus, the UAVs in IoDAV adjust their locations based on the new locations of ground vehicles that allows the IoD nodes to follow the vehicles' movements on the ground and redeploys them accordingly. Besides, the IoDAV tries to keep the RSSI above the threshold value which is -86dBm and then number of covered vehicles is increased. Consequently, it provides a longer connectivity time.

We also compare the normalized coverage for a different set of UAVs (IoD size), and the results are shown in Fig.7a and Fig.7b for sparse and dense scenarios, respectively. It can be noticed that the coverage increases as IoD size increases with the same transmission power used, demonstrating the impact of IoD size on coverage. In the figure, the proposed IoDAV approach achieves better average coverage than other schemes with overall coverage improvements of 48.79% over NIoD and 36.6% over FIoD in the sparse scenario, while

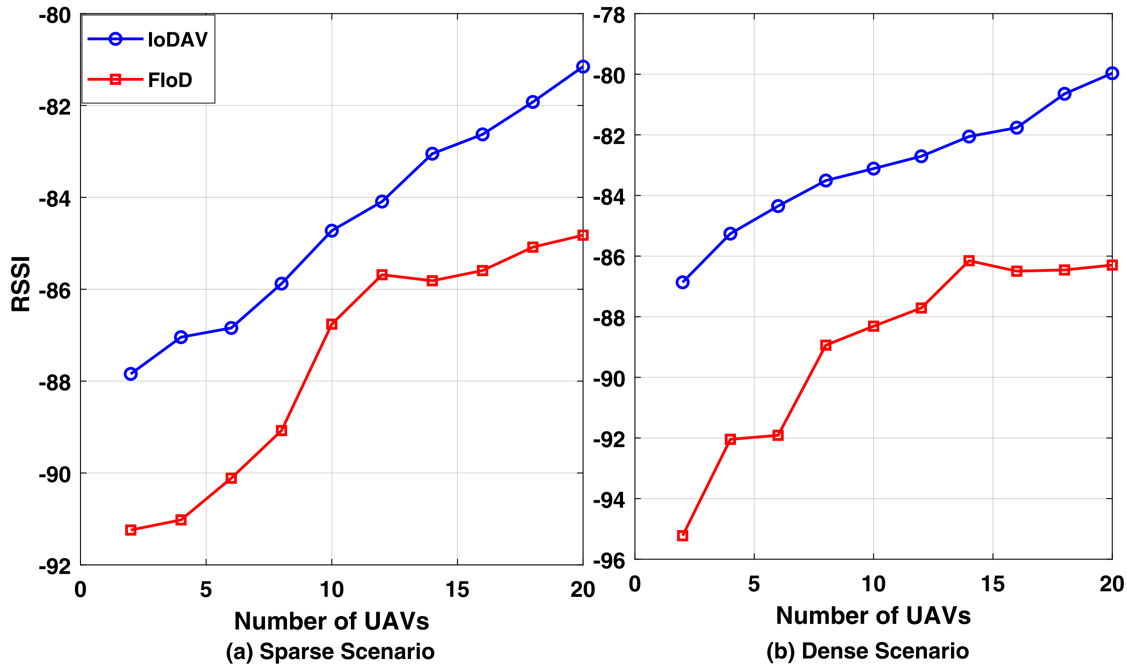


FIGURE 9. Average RSSI at the receiver for different sets of UAVs in IoDAV and FIoD schemes.

for the dense scenario the improvement is 12.9% over NIoD and 4.2% over FIoD. This means that in the dense scenario, the number of isolated vehicles is lower than that in the sparse scenario.

The experiment distribution results can be observed throughout the Box-plot in Fig.8. As figure 8 illustrates, IoDAV plot-box indicators are higher than other schemes. The highest coverage achieved by IoDAV is 100% which represents superior to the upper bound of the other schemes. It also shows that NIoD and FIoD in the worst case are inefficient since the coverage is lower than 30% and 51%, respectively, but still not higher than IoDAV. Moreover, half of IoDAV is higher than 90% which is higher than other schemes. It turns out that Box-plot shows the superiority of IoDAV to other approaches. IoDAV has great superiority in all indicators compared with other competitors.

To further investigate the performance of the proposed IoDAV deployment model, we discuss the impact of IoD size on RSSI at the receiver side, which is considered an indicator of key performance. Particularly, RSSI is measured with respect to the simulation time and the average RSSI for both FIoD and IoDAV are presented in Fig.9a, and Fig.9b for sparse and dense scenarios, respectively.

As discussed above, the positions of UAVs in FIoD are fixed, i.e UAVs are hovering in their deploying places during the whole mission time, and neglect the movements of vehicles on the ground. Furthermore, the vehicles are moving, which implies that there are non-uniform densities of cars at a different time in the given region. Therefore, the whole region can't be covered with the available number of fixed drones and thus all vehicles cannot be covered. As a result, the fixed UAVs become far from ground vehicles as they move which in turn reduces the RSSI while the dynamic IoD or IoDAV can cope with the updating of vehicles locations and then tries to keep the RSSI above threshold value which is −86dBm as exhibited in the figure. It turns out that the proposed IoDAV has the most consistent result.

VIII. CONCLUSION

In this work, we developed a novel dynamic collaborative IoDAV model in which UAVs connect isolated vehicles on the ground with each other. We proposed an optimization approach, an improved version of particle swarm optimization, to optimally deploy IoD to provide communication among vehicles on the ground. Depending on the vehicles' locations at any instant, IoD nodes were deployed to provide optimal connectivity for the isolated vehicles. Furthermore, the signal quality received at the car's receiver was utilized to assess the best IoD location to maximize connectivity. The RSSI was obtained via simulation by using the Two Ray Ground Reflection model. Two scenarios were considered in this paper: sparse and dense scenarios. More importantly, the results were compared with the standard VANET and FIoD models. The results illustrated that the proposed IoDAV approach outperformed other schemes. This is because the dynamic model used in IoDAV could cope with a dynamic environment of ground vehicles and achieved better coverage than both standard VANET and FIoD models during the whole simulation time.

In future work, we intend to study the influence of other propagation models such as Nakagami Fading.

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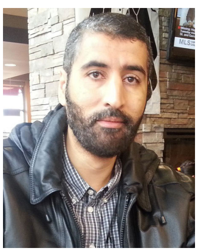

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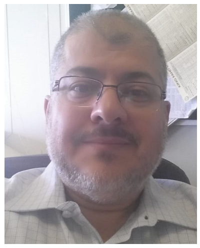

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